Towards AI-assisted neutrino theory design

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ABSTRACT

The process of model building in particle physics requires a physicist to perform a series of complex tasks. They must select symmetry groups, determine field content, assign representations, construct the Lagrangian, compute the predictions of this model and, after fitting the free parameters, evaluate the model's compatibility with observed data. This process is constrained by the physicist's time and their intuition with mathematically complex groups, developed over years of experience. We develop an Autonomous Model Builder (AMBer), capable of performing all of these steps to find elegant neutrino models using reinforcement learning with physics feedback. AMBer rapidly explores a space of fields, symmetry representations and interacts with physics software to calculate the predictions of its proposed models, fitting free parameters to observed data. It is able to find theories with few free parameters that are as compatible with experimental observations. With AMBer, we can explore new symmetry groups for neutrino model building that have not been considered, and for which neutrino physicists have yet to build intuition, in a fraction of the time it would take by hand or through brute-force search.

Introduction

Particle physics seeks answers to basic questions about the nature of matter and its interactions. These answers are not in the form of raw experimental results, but expressed as a *models* of particles and their interactions that match observations and make predictions for novel phenomena. In the case of neutrino oscillations, for example, a successful model should explain the observed neutrino masses and oscillations with minimal additional theoretical elements.

Building such a model is far from trivial, as the space of theoretical options is vast while the experimental results are typically highly constraining. At the same time, the twin goals of achieving agreement with experiment and minimizing degrees of freedom are often in tension. Complicating matters further, the space itself is not conducive to systematic searches, as small changes in model content or structure can yield dramatic changes in quality, for example. In the case of neutrino models, there is the additional challenge that individual models take significant work to evaluate: proposing a set of symmetries and fields, assigning representations of these symmetries to the fields, and performing intricate calculations to determine the predictions of a new model.

The typical approach relies on theorists to use their experience and inspiration to select and evaluate bespoke theories, each of which requires significant effort. In the context of neutrino models, the result is a large space that is expensive to explore, containing vast regions which have not been thoroughly considered. Within these spaces may lie novel, beautiful, simple explanations of our Universe. We interface a reinforcement learning agent with an end-to-end optimized physics software pipeline to automatically explore this space.

1 Model Building with RL

In the model-building recipe, several steps are either cumbersome, require human intervention or are computationally intensive. Specifically, the calculation of the superpotential, the mass matrices and the parameter fit are bottlenecks that prevent rapid evaluation of a specific model. To enable an efficient search, an optimized software pipeline is developed to allow automated end-to-end evaluation of a model. Existing scientific software such as `Discrete`[1], written in Mathematica, is translated into `PyDiscrete` for some of the key features of `Discrete`. The symbolic calculation of the lepton and neutrino mass matrices

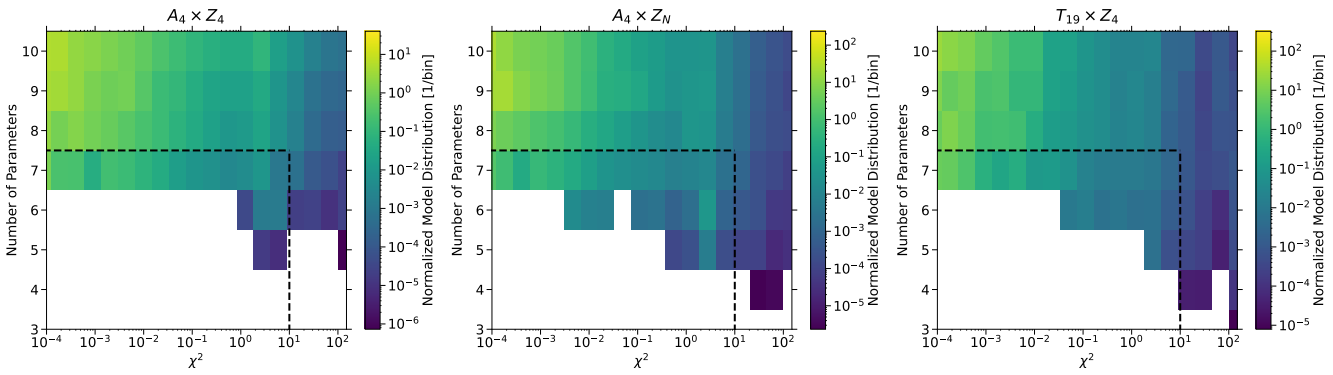

Figure 1. Number of parameters and χ^2 for a representative distribution of found models for the three theory spaces searched: $A_4 \times \mathbb{Z}_4$(left), $A_4 \times \mathbb{Z}_N$ (middle), and $T_{19} \times \mathbb{Z}_4$ (right). The region within the dashed black lines contains models with ≤ 7 parameters, and good fits, $\chi^2 < 10$.

was automated with a python package `Model2Mass`. Fitting the free parameters to observables requires minimizing the χ^2 over a large parameter space that features many local minima. The `FlavorPy` package is used for this task.

An reinforcement learning (RL) agent is trained with Proximal Policy Optimization (PPO)[2] to interface with the software pipeline and design new neutrino models. It observes the current proposed model and is allowed several actions to change the particle content or symmetry content of the model, and over time learns to find good models that have a good fit to data and few free parameters.

2 Results

AMBer finds too many good models to describe each one in detail, so broad features are highlighted, and selected individual models analyzed in further detail.

Three theory subspaces are considered. They can be classified according to the flavor symmetry group and the maximum number of allowed flavons, n_{ϕ_i}, allowed: $A_4 \times \mathbb{Z}_4$, $n_{\phi_i} \leq 5$, $A_4 \times \mathbb{Z}_N$, $n_{\phi_i} \leq 5$, and $T_{19} \times \mathbb{Z}_4$, $n_{\phi_i} \leq 6$, where the upper bound on the number of flavons is motivated by models currently considered in the literature for A_4, while for T_{19}, $n_\phi \leq 6$ is chosen such that AMBer has the ability to place one model in each triplet representation, if it chooses to. AMBer identifies a large number of viable models, particularly those with more than 8 parameters and a small $\chi^2 < 1$. In Figure 1, the distribution of the number of parameters and χ^2 values is shown for a representative sample of these models. AMBer finds many models which are predictive ($n_p \leq 7$) and well fit to data ($\chi^2 < 10$), which is denoted by the region bounded by the dashed black line.

A particularly simple model is shown in Tab. **??**, with only 4 free parameters and $\chi^2 \approx 10$. The relevant mass terms in the Lagrangian for this model can be written in the mass basis, after the flavons acquire a vaccum expectation value (VEV), as

$$m_C = v_d\,\hat{\alpha}_C \begin{bmatrix} 1 & \alpha_2 & \alpha_1 \\ 1 & -\alpha_2(\frac{1}{2}-\frac{\sqrt{3}}{2}i) & -\alpha_1(\frac{1}{2}+\frac{\sqrt{3}}{2}i) \\ 1 & -\alpha_2(\frac{1}{2}+\frac{\sqrt{3}}{2}i) & -\alpha_1(\frac{1}{2}-\frac{\sqrt{3}}{2}i) \end{bmatrix}, \quad m_M = \Lambda\hat{\alpha}_M \begin{bmatrix} \alpha_3 & 0 & \frac{1}{2} \\ 0 & \alpha_4 & 0 \\ \frac{1}{2} & 0 & 0 \end{bmatrix}, \quad m_D = v_u\hat{\alpha}_D \begin{bmatrix} 0 & 0 & -1-\sqrt{3}i \\ -1+\sqrt{3}i & 0 & 0 \\ 0 & 2 & 0 \end{bmatrix} \tag{1}$$

where the $\hat{\alpha}_i$ is a normlalization that is independent of the fit, because only dimensionless mass ratios are fit.

Conclusion and Outlook

Particle physics model building has traditionally relied on a physicist's intuition to explore fields and the symmetries they obey to describe the Universe we observe. However, this mathematical space is vast and a majority of it remains completely unexplored. AMBer, an end-to-end systematized, AI-assisted method to explore patterns in this high-dimensional discrete space by leveraging reinforcement learning and high-performance computing is presented here. By leveraging existing scientific software, developing novel software, and redesigning existing software for efficiency, an end-to-end pipeline for neutrino model building is built and interfaced with the RL agent. AMBer finds new and interesting models, and has helped us explore properties of a completely new symmetry, T_{19}, that can be used for neutrino model building. A vast space of future work is foreseen in RL-assisted theoretical physics model building and potential cross-pollination with AI for theorem proving community.

References

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